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Self-reported versus GPS-derived indicators of daily mobility in a sample of healthy older adults

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ABSTRACT

In light of novel opportunities to use sensor data to observe individuals' day-to-day mobility in the context of healthy aging research, it is important to understand how meaningful mobility indicators can be extracted from such data and to which degree these sensor-derived indicators are comparable to corresponding self-reports. We used sensor (GPS and accelerometer) and self-reported data from 27 healthy older adults (≥67 years) who participated in the MOASIS project over a 30-day period. Based on sensor data we computed three commonly used daily mobility indicators: life space (LS), travel duration using passive (i.e., motorized) modes of transportation (pMOT) and travel duration using active (i.e., non-motorized) modes of transportation (aMOT). We assessed the degree to which these sensor-derived indicators compare to corresponding self-reports at a within-person level, computing intraindividual correlations (iCorrs), subsequently assessing whether iCorrs can be associated with participants' socio-demographic characteristics on a between-person level. Moderate to large positive mean iCorrs between the respective self-reported and sensor-derived indicators were found (r = 0.75 for LS, 0.51 for pMOT and 0.36 for aMOT). In comparison to sensor-derived indicators, self-reported LS slightly underestimates, while self-reported aMOT as well as pMOT considerably overestimate the amount of daily mobility. Participants with access to a car have higher probabilities of agreement in the pMOT indicator. Sensor-based assessments are promising as they are "objective", involve less participant burden and observations can be extended over long periods. The findings of this paper help researchers on mobility and aging to estimate the magnitude and direction of potential differences in the assessed variable due to the assessment methods.

1. Introduction

In light of the aging of many societies, it becomes increasingly important to study factors that contribute to individuals leading an active and independent life up to old age. An increasing number of studies show that there are relations between people's spatial mobility patterns and their level of health, well-being and independence (Giannouli et al., 2018; Hirsch et al., 2016; Kaspar et al., 2015; Polku et al., 2015; Prins et al., 2014; Takemoto et al., 2015). The mixture of transport modes used, distances covered and spatial extent of daily out-of-home activities can be related to the level of independence as well as mental and physical health of older adults.

Life space is a concept often used in aging research to capture the spatial extent of older adults' daily mobility. It has been shown to be predictive of different health outcomes in both community-dwelling healthy as well as cognitively impaired older adults, including cognitive ability (Tung et al., 2014), physical activity (Rosso et al., 2013), and functional ability (Uemura et al., 2013). Mobility is typically evaluated using measures such as life-space questionnaires (LSQ) asking people whether and how often during a predefined preceding period (e.g., 1 month) they traveled to hierarchically nested, ordinal levels of increasing spatial areas (e.g., home, yard, immediate neighborhood, town, etc.) (Peel et al., 2005).

While it is easy for participants to report whether these broad semantic categories of spatial area have been visited or not during the defined period, we would argue that distance covered by or duration spent on traveling are much more accurate proxies for people's daily mobility. Especially for (cognitively) healthy older adults who are barely constrained in their mobility potential, we argue that the effective duration that a person has traveled and therefore been exposed to various environments is a more informative indicator, with greater implications for that person's learning opportunities and in turn health-

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related benefits than the spatially less fine-grained LSQ.

In a health context, it is furthermore interesting to distinguish between travel using passive (motorized) and active (non-motorized) modes of transportation (MOT). Usage of active modes of transportation (aMOT) positively influences the total amount of performed physical activity (Carlson et al., 2015; Costa et al., 2015; Vanwolleghem et al., 2016). Moreover, the properties of the environment experienced by moving from one destination to another differs depending on the MOT used (Cetateanu et al., 2016; Chaix et al., 2013). Typically, research from the field of transport planning deals with the assessment of how much individuals travel using different MOT. Therefore, researchers traditionally relied on travel diaries with chronological reports of trips undertaken including origin, destination and MOT over a defined period (e.g., 1 week) (Panter et al., 2014; Richardson et al., 1995).

In the health sciences, GPS devices are becoming increasingly popular to objectively assess continuous, fine-grained and person-specific descriptors of individuals' mobility, thereby addressing problems arising with traditional self-reported measures such as generalized responses, as well as retrospective and social desirability biases (Birenboim and Shoval, 2016; Blanchard et al., 2010). Moreover, sensors provide information on mobility behaviors of individuals who are limited in giving valid self-reports (e.g., due to cognitive impairment). There is a wide range of methods to extract different indicators of mobility from sensor data (Perchoux et al., 2014). Commonly used methods to derive life space (in the spatial sciences also referred to as *activity space*) from GPS data are the *standard deviational ellipse* or *minimum convex polygon* (Hirsch et al., 2014). Deriving MOT from GPS and/or accelerometer data commonly employs machine-learning (Cetateanu et al., 2016; Ellis et al., 2014) or rule-based algorithms (Schuessler and Axhausen, 2009; Vanwolleghem et al., 2016). However, sensor-derived indicators also have limitations such as data outage due to GPS signal loss (e.g., in buildings) or technical issues originating from the sensing device. Moreover, many classification algorithms depend on the quality of training data or subjective thresholds.

To interpret mobility data in their own right and in relation to health, as well as to compare studies using self-reported variables to studies using sensor-derived variables, it is crucial to know to which degree different indicators agree. There is a wide range of research in the domain of physical activity investigating associations between sensor-derived (objective, direct) and self-reported (subjective, indirect) measures (Prince et al., 2008). Within the spatial sciences, however, mainly researchers interested in transportation have investigated how trips reported in travel diaries correspond to trips extracted from GPS data (Houston et al., 2014; Nguyen et al., 2017; Stopher and Shen, 2011). Otherwise, little work has compared self-reported and sensor-derived indicators of mobility (Klous et al., 2017; Shareck et al., 2013; Vanwolleghem et al., 2016).

We intend to contribute to closing this gap by showing how commonly used self-reported measures of mobility (LS, pMOT, aMOT) can be extracted from GPS data and addressing the following research questions: First, to what degree do sensor-derived daily mobility indicators and their corresponding self-reports agree? Second, to what degree are different types of mobility indicators corresponding to each other? Third, do certain socio-demographic and mobility-relevant characteristics of participants have an impact on the degree of agreement between self-reported and sensor-derived mobility indicators?

2. Methods

2.1. Data and preprocessing pipeline

We use data from 27 community-dwelling older adults who participated in Phase 1 of the Mobility, Activity and Social Interaction Study (MOASIS) over a period of 30 days (Röcke et al., n.d.; Bereuter and Weibel, 2016). In the MOASIS project, data are collected using a custom-built device called uTrail (featuring, amongst others, a GPS and accelerometer), as well as different self-reported health-related variables in a sample of community-dwelling older adults with no clinically relevant cognitive impairments or depressive symptoms in the German-speaking part of Switzerland. The overarching goal of MOASIS is to identify individual profiles of daily-life activities and to investigate the associations between these and various indicators of health and psychological functioning, both in terms of differences between and within individuals.

We used 30-day GPS (1 Hz sampling interval, Fastrax GPS antenna UC530) (U-blox, 2013) and accelerometer (3 Hz sampling interval, LSM303D module) (ST-Microelectronics, 2013) data assessed with the uTrail. Participants' 30-day data were segmented into daily units using the date (midnight) as separation criterion between person-days. We further included the daily self-reported indicators of life space, and duration of traveling using pMOT as well as aMOT from the end-of-day diary. Finally, we included several socio-demographic variables assessed with a baseline questionnaire that preceded the observation period. All of the processing and the analyses of the data were done in R (v. 3.3.1, 2018). Specifically, we used *plyr*, *dplyr*, *reshape*, *sp*, *rgeos*, and *raster* for data manipulation; *ggplot2* for graphs; and *psych*, *MASS*, and *corrplot* for the statistical models. Maps were created in QGIS (v2.10.1, 2018).

The data cleaning pipeline is illustrated in Fig. 1. It shows numbered steps at which invalid person-days were excluded from the analysis. The steps are explained in more detail throughout this section. The dataset consisted initially of 795 person-days (26 participants with 30 days, 1 participant with 15 days due to early study drop-out). In Step 1, we excluded the first and last day of each participant because these days typically featured incomplete self-reports and/or sensor data. This left us with 741 days.

2.2. Self-reported measures

2.2.1. Daily self-reported life space (LS)

Participants were asked to complete the LSQ using the life-space (LS) levels proposed in Stalvey et al. (1999) adapted to the Swiss context (see Supplementary Material – Part A for the original questions). The individual levels (a)-(h) are illustrated in Fig. 2. For every study day, participants reported whether they had attained each of these levels. As levels (e) and (f) were not defined in a sufficiently discriminable way, they were merged to one joint level. Likewise, levels (a) and (b) were merged as they are not distinguishable solely based on GPS data. The resulting six categories were assigned numbers 1 to 6. The category of the maximum LS level attained per day represents the self-reported daily life-space of each participant. The number of responses per participant for this item ranged between 9 and 28 ($M = 26.2$). This resulted in 707 days with valid responses for daily self-reported LS across all participants (−34 days; Step 2, Fig. 1).

2.2.2. Daily self-reported pMOT and aMOT

Participants' daily estimates of duration of traveling using pMOT and aMOT, respectively (reported in [h and min] and converted to [min] for analysis) are used as daily self-reported indicators of pMOT and aMOT, respectively (see Supplementary Material – Part A). Passive MOT include spatial displacements undertaken using motorized means of transport such as a private car or a public means of transport. Active MOT include non-motorized ways of outdoor spatial displacements such as walking or cycling. The number of responses per participant for both items ranged between 12 and 28, with means of 25.6 and 25.4 for pMOT and aMOT, respectively. This resulted in a total of 691 (pMOT) and 686 (aMOT) valid days (−50 and −55 days, respectively; Step 2, Fig. 1).

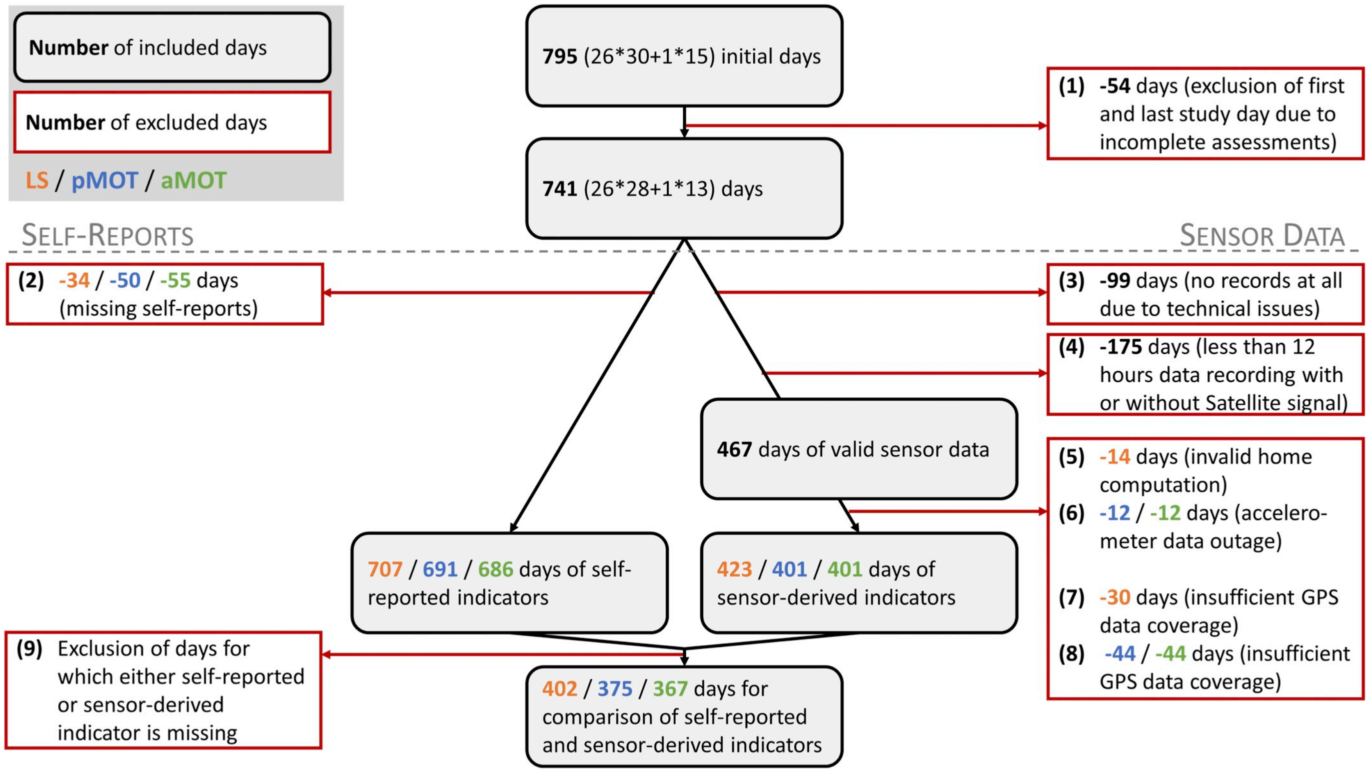

Fig. 1. Schematic representation showing the data cleaning for each of the self-reported and sensor-derived mobility indicators (LS, pMOT, aMOT). Grey filled boxes with rounded corners show the number of remaining person-days after each filtering step, given in the red boxes. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

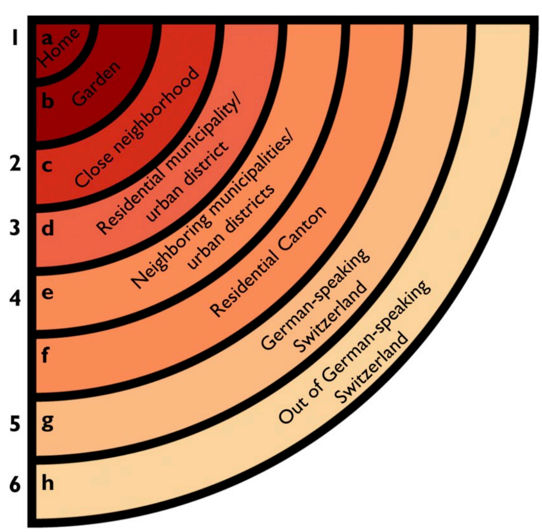

Fig. 2. Conceptual model of the life-space questionnaire adapted to the Swiss-German context. Level (b) includes the participant's close surrounding area (e.g., garden, balcony). Close neighborhood (level (c)) was defined as within 1 km from home. For analysis, levels a) and b) as well as levels e) and f) have been merged to one level.

2.2.3. Socio-demographic variables

From the MOASIS baseline questionnaire, we included the following variables:

- gender (0 = male, 1 = female);
- chronological age;
- highest level of education (1–8: increasingly higher education level), reclassified into low-education (1–3: "no school", "obligatory school" and "professional training") and high-education (4–8: "university-entrance diploma", "university" and other categories representing education beyond professional training);
- monthly income (1–6: increasingly higher income level), reclassified into low-income (1,2: ≤4000 CHF), middle-income (3,4: > 4000 CHF and ≤8000 CHF) and high-income (5,6: > 8000 CHF);
- availability of a car in the household (0 = no, 1 = yes).

Income classes were formed such that the median gross monthly salary of a Swiss jobholder of 6427 CHF lies approximately in the middle of the middle-income class (Swiss Federal Statistical Office (FSO), 2014).

2.3. Sensor-derived measures

2.3.1. Preprocessing sensor data

Mainly due to memory capacity problems of the uTrail devices, 99 days out of the original 741 did not feature any recordings and were therefore missing (Step 3, Fig. 1). In order to only include days with as complete information of individuals' daily mobility as possible, we additionally excluded days with less than 12 h of recording (irrespective of satellite signal). Comparable studies typically chose comparable albeit slightly less conservative thresholds for a day to count as valid (e.g., 10 h in Tsai et al., 2016 or Vanwolleghem et al., 2016). Based on this additional incomplete data criterion an additional 175 person-days were removed, leaving us with 467 valid person-days for sensor-derived indicators (Step 4, Fig. 1).

As a prerequisite for the LS computation, the home location of each participant was derived from the GPS data (Supplementary Material – Part B). The home computation of two participants could not be reliably detected due to a combination of technical issues (data outage, poor GPS reception at home) and several nights not spent at home. They were consequently excluded from further analyses involving the sensor-derived life-space indicator (−14 person-days; Step 5, Fig. 1).

Table 1
Spatial definition of the life-space levels.

No.	Life-space (LS) level	Spatially defined category
1	a) Home/b) Garden	Circular buffer of 150 m
2	c) Close neighborhood	Circular buffer of 1000 m
3	d) Residential municipality	Municipality containing home
4	e) Neighboring municipalities/f) Residential Canton	Canton that contains home
5	f) German-speaking Switzerland	German-speaking municipalities of Switzerland
6	g) Further away	Area beyond Level 5

Moreover, due to accelerometer data outage during the first half of the study of another participant, 12 person-days were excluded from further analyses involving sensor-derived MOT indicators, as these depend on both the GPS and accelerometer data (Step 6, Fig. 1).

2.3.2. Daily sensor-derived life space

To extract an indicator approximating the daily LS from the GPS data, we identified the most distant LS category that was attained each day. For this purpose, as shown in Table 1, we assigned the LS categories to increasingly distant spatial areas around a participant's home location similarly to Wan and Lin (2013). Levels 1 and 2 were computed using circular distance buffers and Levels 3–6 made use of the administrative unit boundaries provided by the Swiss Federal Office of Topography (2015) in conjunction with data on the dominant language of each municipality provided by the Swiss Federal Statistical Office (2016). Fig. 3 shows the spatially defined LS levels of two exemplary days for one participant.

Each GPS fix was assigned the most distant LS level that it was contained in. Eventually, the daily sensor-derived LS level was represented by the maximum LS level that contained at least 300 GPS fixes (which corresponds to a stay of at least 5 min in this level). A threshold of 5 min ensured that participants spent a sufficiently long time at a particular location to remember it and avoided an overestimation of the LS indicator due to individual inaccurate GPS positions. A 5-min threshold is also commonly used for algorithms aiming at detecting meaningful activity locations in GPS data (Thierry et al., 2013; Wan and Lin, 2013). 30 person-days did not fulfill this criterion for any of the six levels and were therefore excluded from analysis involving the sensor-derived LS (n = 423 remaining person-days; Step 7, Fig. 1).

2.3.3. Daily sensor-derived pMOT and aMOT

To compute daily durations of travel using passive and active MOT based on the GPS and accelerometer data, we followed the 4 steps visualized in Fig. 4 and described in detail in the Supplementary Material – Part C. Applying these processing steps, 44 person-days were excluded from further analysis as the respective days did not feature enough GPS data with satellite coverage to compute the MOT indicators (n = 401 remaining person-days; Step 8, Fig. 1).

2.4. Selectivity analysis

The statistical analyses (described in the next section) are based on person-days for which both a valid self-reported and a sensor-derived indicator are available (n = 402 (LS), n = 375 (pMOT), n = 367 (aMOT); Step 9, Fig. 1). Around half of the initial 795 person-days were excluded by the preprocessing pipeline. This proportion lies within a range comparable to other studies involving real-life sensor-based assessments (e.g., Demant Klinker et al., 2015; Isaacson et al., 2016; Panter et al., 2014). To gain more insight into excluded days, we carried out a selectivity analysis (see Supplementary File – Part D), comparing days with missing sensor data (excluded days) to days with available sensor data (included days) in terms of the distribution of the three self-reported mobility indicators of interest (LS, pMOT, aMOT). The analysis shows that the distribution of the self-reported mobility indicators looks almost identical for included and excluded study days. Therefore, days with missing data seem not to be systematically linked to days with a specific mobility behavior and the results of the comparisons are generalizable to days that have been excluded.

2.5. Statistical analyses

We computed several descriptive statistics to capture deviations, respectively agreement between self-reported and sensor-derived indicators. These are based on the subtraction of the sensor-derived from the self-reported indicators. Based on these differences, we further evaluated how many person-days of each indicator fall into one of the following three categories defined by the thresholds presented in Table 2: days with agreement in reporting, self-reported under-reporting (resp. sensor-based over-reporting), and self-reported over-

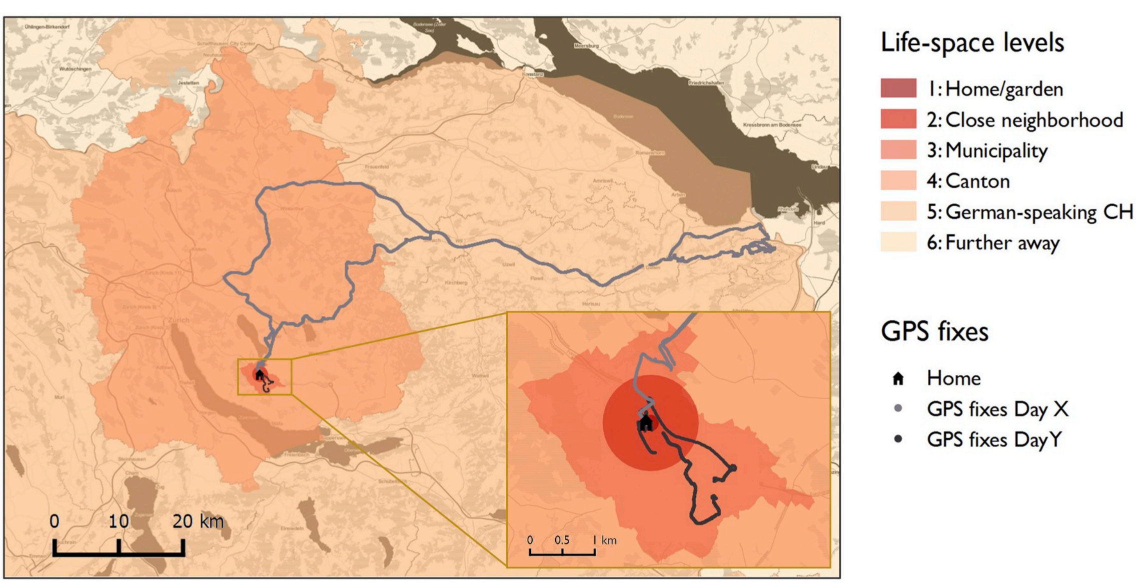

Fig. 3. Spatially defined life-space levels of one of the participants with the GPS fixes of two exemplary days. Based on the intersection of the respective GPS fixes with the life-space levels, Day X and Day Y would be assigned the daily sensor-derived LS Levels 5 and 3, respectively.

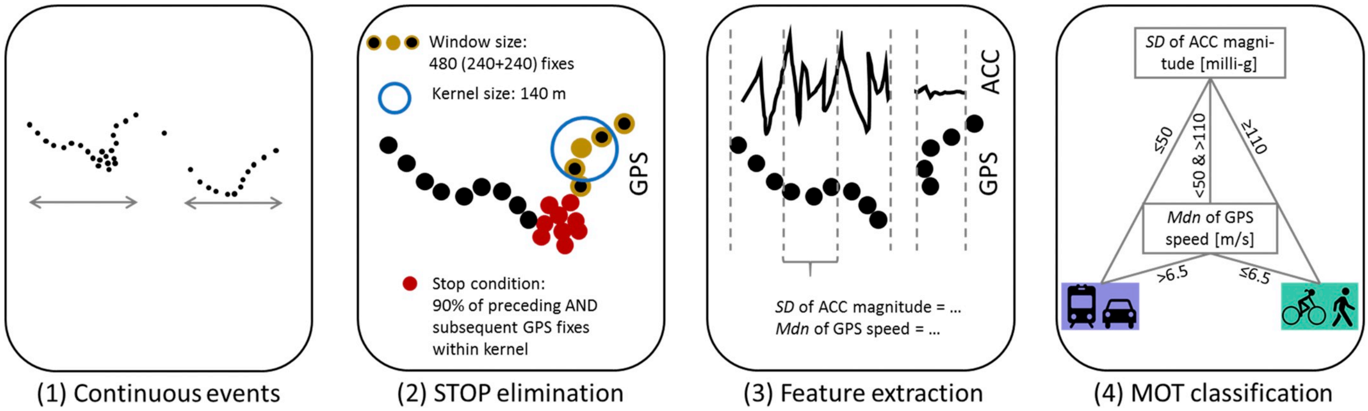

Fig. 4. Pipeline of MOT detection. (1) Detection of continuous events with temporal gaps of maximum 120 s, (2) elimination of stop fixes based on a threshold for spatio-temporal density, (3) computation of statistical features for 1-min move segments, (4) classification of 1-min segments based on thresholds.

Table 2
Classification of the person-days to days of agreement in reporting, self-reported under-reporting and self-reported over-reporting.

	Δ LS indicators	Δ pMOT/aMOT indicators
Agreement in reporting	± 1 level	± 10min
Self-reported under-reporting	< 1 level	< 10min
Self-reported over-reporting	> 1 level	> 10min

Note. Classification is based on the difference between the corresponding self-reported and the sensor-derived indicators (Δ indicators).

reporting (resp. sensor-based under-reporting). As in Houston et al. (2014), we chose 10 min as an acceptable difference to classify self-reported and sensor-derived pMOT/aMOT indicators as being in agreement. For ease of reading, we use the terms self-reported under- and over-reporting in the remainder of the paper, being aware that the reasons for the deviations could equally well be caused by the sensors' under- and over-reporting, respectively. To obtain detailed information regarding the degree of agreement for individual LS levels, we furthermore calculated a confusion matrix.

Moreover, we computed intraindividual correlations (iCorr) for all pairwise combinations of the six mobility indicators as a measure of within-person associations between all pairs of mobility indicators over the day-to-day reporting period. The resulting person-specific correlation coefficients indicate for each person the direction and strength of how information from two different mobility indicators relates to one another (e.g., are days with higher self-reported LS also days with higher sensor-derived LS for a given person?). The person-level iCorrs were then averaged across persons to obtain mean within-person association (mean iCorr) for different comparisons of mobility indicators. We only included pairwise complete cases for the respective indicator comparisons to compute the correlation values.

We used Cohen's (1988) convention to interpret the strength of the associations. Hence, correlation coefficients between 0.10 and 0.29 were considered small, between 0.30 and 0.49 moderate, and ≥0.50 large correlations. We used Spearman's correlations because LS indicators are categorical and MOT indicators (according to the Shapiro-Wilk normality test) were found to be non-normally distributed. Finally, we investigated whether any of the socio-demographic factors (gender, age, education, income, or availability of a car) were correlated with participants' estimation accuracies approximated by the above-mentioned iCorr values. That is, we investigated whether the person-based iCorrs (reflecting the degree of correspondence between sensor-derived and self-reported data) for the three indicators LS, pMOT, and aMOT were related to individuals' socio-demographic characteristics.

3. Results

Following a short presentation of the characteristics of the study participants, Sections 3.2 to 3.4 are devoted to reporting the results with respect to the three research questions posed in the Introduction.

3.1. Characteristics of study participants

Of the 27 participants, 55.6% were female. Average age was 72.3, with a range from 67 to 81 years. Five participants had an income of less than 4000 CHF (low-income), 18 participants between 4001 and 8000 CHF (medium-income) and 3 more than 8000 CHF (high-income) per month (1 missing value). The ratio between study participants having access to a car to the ones who did not was 19 to 8. The high-education group consisted of 21 out of 27 participants.

Table 3 shows the descriptive statistics for the 6 different mobility indicators. Self-reported and sensor-derived measures indicate an average LS Level of 4 (i.e., within the Cantonal borders). For pMOT and aMOT, the sensors indicated average daily travel durations of 38 (pMOT) and 37 (aMOT) minutes whereas the self-reports indicated considerably higher average daily travel durations of 60 (pMOT) and 90 (aMOT) minutes. Overall statistical distributions of sensor-derived and self-reported LS indicators are almost identical, whereas self-reported MOT indicators yield approximately 2–3 times higher values than their corresponding sensor-derived measures.

3.2. Agreement between corresponding self-reported and sensor-derived indicators

3.2.1. Life space

Table 4 shows the confusion matrix for the 402 person-days for which both a valid GPS-derived and self-reported indicator were available (Fig. 1). The rate of exact agreement between GPS-derived and the self-reported LS indicators is high (58%, colored diagonal values). This is also reflected in the median difference of 0.0 between self-reports and sensor-derived measures (Table 5).

Table 3
Descriptive statistics of the different mobility indicators.

	Min	Median	Mean	Max	N
(1) LS (sensor) [level]	1	4	4	6	423
(2) LS (report) [level]	1	4	4	6	707
(3) pMOT (sensor) [min]	0	38	50	314	401
(4) pMOT (report) [min]	0	60	94	1260	691
(5) aMOT (sensor) [min]	0	37	46	301	401
(6) aMOT (report) [min]	0	90	119	750	686

Table 4
Confusion Matrix of self-reported versus sensor-derived life-space indicators (n = 402).

		Self-reported						
	Level	1	2	3	4	5	6	Precision
Sensor-derived	1 (Home/ Garden)	11	3	2	5	0	2	0.48
	2 (Close neighborhood)	12	17	25	2	0	1	0.30
	3 (Municipality)	0	4	13	1	1	0	0.68
	4 (Canton)	0	4	53	91	1	0	0.61
	5 (German-speaking Switz.)	0	2	9	23	70	3	0.65
	6 (Further away)	0	0	1	1	14	31	0.66
	Recall	0.48	0.57	0.13	0.74	0.81	0.84	**0.58**

Note. The diagonal values are the number of person-days that agree for the respective LS levels. The numbers in small fonts represent recall and precision values for the different LS levels. We use the terms 'recall' and 'precision' that are normally used when comparing predicted values to an available ground truth. Here, we use these terms to be able to refer to them distinctively and without the intention of implying that either self-reported or sensor-derived indicators should be seen as ground truth. The overall accuracy is given in bold font.

Table 5
Summary statistics for deviations between self-reported and sensor-derived indicators.

	Min	Median	Mean	Max	N
LS [level]	−3.0	0.0	−0.2	5.0	402
pMOT [min]	−104.0	25.0	54.7	603.0	375
aMOT [min]	−99.0	45.0	72.5	737.0	367

According to Table 4, lower recall values are obtained for Levels 1–3 (i.e., the levels closer to one's home) than for the higher Levels 4–6 (i.e., the levels more distant to one's home). This means that the lower self-reported LS levels are less likely to be correctly reproduced by the sensor-derived measures. The precision values (representing the probability that a given sensor-derived level will correspond to the corresponding self-reported value) are more evenly distributed, with lowest values for Levels 1 and 2. These two levels therefore have a lower likelihood to be correctly inferred from a sensor-derived indicator. The sensor-derived Level 2 was often reported as one of the adjacent Levels 1 or 3.

For cases in which the two indicators disagreed, however, there was a tendency for participants to underestimate rather than overestimate the size of their LS based on the self-reported LSQ (31% lower-left vs. 11% upper-right off-diagonal values). However, most deviations between self-reported and GPS-derived indicators are within ± 1 level. In fact, 93% of instances have deviations of maximally 1 level (Table 6).

3.2.2. pMOT and aMOT

We included 375 and 367 valid person-days for the comparison of self-reported and sensor-derived pMOT and aMOT, respectively (Fig. 1). Table 5 shows that the mean (*M*) and median (*Mdn*) difference between self-reported and sensor-derived indicators are higher for active (*M* = 72.5 min, *Mdn* = 45.0 min) than for passive (*M* = 54.7 min, *Mdn* = 25.0 min) MOT. Both, however, clearly show that self-reports estimate higher durations on average. From the distribution statistics of deviation values, it is discernible that they are both skewed to the right (*Mdn* < *M*), with most of the values around 0. However, clearly more deviations are positive, implying more person-days with self-reported overestimated durations. In Table 6, we counted instances of person-days with agreement in reporting (i.e., difference of maximum ± 10 min), self-reported under- and over-reporting. We found that self-reports overestimate the duration in 59% and 72% of the instances for pMOT and aMOT, respectively. Self-reported and sensor-derived indicators agreed in 23% (pMOT) and 13% (aMOT) of the person-days.

Table 6
Person-days [number (percent)] with agreement between self-reported and sensor-derived indicators, self-reported under-reporting, and self-reported over-reporting (see Table 2 for definition of agreement).

	Agreement	Under-rep.	Over-rep.	N
LS	372 (93%)	17 (4%)	13 (3%)	402 (100%)
pMOT	86 (23%)	66 (18%)	223 (59%)	375 (100%)
aMOT	46 (13%)	57 (16%)	264 (72%)	367 (100%)

3.3. Comparisons across all mobility indicators

Table 7 shows descriptive statistics of iCorr values for comparisons between all the combinations of the six mobility indicators. The number of person-days included in each comparison varies between 367 and 685. For most comparisons, it was possible to include days from all the 27 participants (each contributing between 5 and 28 comparison days). Two participants were excluded from all comparisons involving the sensor-based LS indicator due to the invalid home computation mentioned in Section 2.3.1. One additional participant was excluded from the comparison of the sensor-based LS indicator to the two indicators sensor-based pMOT and sensor-based aMOT due to lacking variance in one of the indicators of the respective comparison cases.

Correlations comparing self-reported and sensor-derived indicators representing the same construct are framed in black in Table 7. A high average iCorr of 0.51 (*SD* = 0.30) and a moderate average iCorr of 0.36 (*SD* = 0.29) were found for pMOT and aMOT, respectively (Table 7). The mean within-person correlation (iCorr) between self-reported and sensor-derived LS indicators was 0.75 (*SD* = 0.16). The *M* and the *SD* of the iCorr values in Table 7 reveal that, except for the correlation between self-reported pMOT and aMOT, all mobility indicators have positive average within-person correlations. The iCorr values shown in green are positive for the majority or all of the participants since subtracting the *SD* from the *M* iCorr would still result in a positive value. The GPS-derived as well as the self-reported LS indicators are moderately to largely correlated to sensor-derived and self-reported pMOT (*M* iCorrs between 0.49 and 0.67). A moderate average intraindividual correlation of 0.41 is also found when comparing sensor-derived LS to sensor-derived aMOT (*M* iCorr of 0.41).

3.4. Socio-demographic characteristics associated with estimation accuracies

Table 8 shows to which extent different socio-demographic factors are associated with the intraindividual estimation accuracies (approximated by the iCorrs). The only significant between-person

Table 7
Mean and standard deviation of the intraindividual correlation (M (SD) iCorr) for the different daily mobility indicator comparisons. Framed in black are iCorrs comparing self-reported and sensor-derived indicators representing the same construct. Colored in green indicates that subtracting the SD from the M iCorr results in a positive value.

	LS (sensor)	LS (report)	pMOT (sensor)	pMOT (report)	aMOT (sensor)	aMOT (report)
LS (sensor)	-	0.75 (0.16) *n*=402	0.55 (0.22) *n*=386	0.63 (0.22) *n*=395	0.41 (0.25) *n*=386	0.21 (0.31) *n*=679
LS (report)	-	-	0.49 (0.23) *n*=382	0.67 (0.19) *n*=685	0.22 (0.35) *n*=382	0.25 (0.26) *n*=679
pMOT (sensor)	-	-	-	0.51 (0.30) *n*=375	0.32 (0.34) *n*=401	0.01 (0.29) *n*=367
pMOT (report)	-	-	-	-	0.25 (0.39) *n*=375	0.20 (0.26) *n*=679
aMOT (sensor)	-	-	-	-	-	0.36 (0.29) *n*=367

Table 8
Interindividual correlations between the participants' estimation accuracies reflected by the iCorrs and different socio-demographic characteristics of the participants.

	Gender	Age	Education	Income	Car
iCorr LS	−0.08	−0.15	0.31	0.27	−0.05
iCorr pMOT	0.31	−0.05	−0.01	−0.05	0.37*
iCorr aMOT	−0.31	−0.10	0.31	0.24	0.05

Note. Spearman's correlations were computed. Variable coding: gender (m = 0, f = 1), education (low = 0, high = 1), income (low = 0, medium = 1, high = 2), car (no = 0, yes = 1). The iCorrs are used as proxies of the participants' estimation accuracies for the different mobility indicators. The iCorrs represent the intraindividual correlations between the respective self-reported and sensor-derived corresponding mobility indicators. Level of significance: *$p < .05$.

association was found regarding availability of a car and higher estimation accuracy for pMOT ($r = 0.37$). Significance levels, however, are dependent on the sample size which was small for the analyses on the between-person level as performed in this section ($n = 27$) in contrast to the above performed analyses based on person-days (Cohen, 1988). The following moderate non-significant correlations were found: Being female was associated with higher iCorrs (i.e., estimation accuracies) in pMOT and lower iCorrs in aMOT. Participants of the high-education class had higher iCorrs for LS and aMOT. Also, being part of a higher income group was positively correlated with participants' estimation accuracies for LS and aMOT. For age, little to no correlation to the participants' estimation accuracy was found.

4. Discussion

In light of an increasing number of researchers advocating the use of sensor-based measurements to assess older individuals' mobility and possible implications for their health (Brusilovskiy et al., 2016; Franke et al., 2017; Meijering and Weitkamp, 2016), we addressed the question to which degree these sensor-based measurements are reflecting the same content as the traditionally used self-reported counterparts. Similar to the above presentation of results, the structure of the following Sections 4.1 to 4.3 reflects the three research questions underlying this paper, and is completed by a general discussion of the strengths and weaknesses of the two assessment methods in Section 4.4.

4.1. Agreement between corresponding self-reported and sensor-derived indicators

4.1.1. Life space

In order to derive the life space of an individual we used a combination of circular buffers around the home location as well as administrative boundaries to obtain zones that are reflecting the categories of the LSQ as closely as possible. The use of circular and administrative boundaries might lead to situations in which the area of a lower LS level exceeds the area of a higher LS level. For example, for people living in a small municipality or close to the border of the municipality, Level 2 (circular neighborhood buffer of 1 km) might exceed Level 3 (the municipality boundary). However, this is an inconsistency inherent to the concept of the life space featuring circular buffer-like levels and levels that are best reflected by administrative boundaries (Peel et al., 2005; Stalvey et al., 1999). This inconsistency is equally reflected in both the self-reported and the sensor-derived LS indicator and should therefore not affect the results of our comparisons. However, when it comes to comparing LS indicators across participants, one has to bear in mind that equal values in LS can refer to very different absolute distances from home (e.g., someone living close to a national border could reach Level 6 traveling covering much less distance than someone living far from the border) and thus possibly imply very different learning opportunities and mobility contexts.

Despite justifiable criticism regarding the life-space concept (see Siordia (2016) for a more thorough discussion), life-space assessments are widely applied and prove to be meaningful in studies of aging, mobility, and health (Rosso et al., 2013; Tung et al., 2014; Uemura et al., 2013). Related research (e.g., Hirsch et al., 2014; Tung et al., 2014; Wan and Lin, 2013) exists on how to derive a life-space indicator from GPS data. To our knowledge, however, we are first to compare the self-reported LSQ to a corresponding sensor-derived measure, despite the fact that the need for such comparisons has been explicitly stated (Liddle et al., 2014; Siordia, 2016). We found a high degree of agreement comparing the daily self-reported to the sensor-derived life-space indicators across participants (*M* iCorr = 0.75, *SD* iCorr = 0.16). 58% of the participants had completely agreeing self-reported and sensor-derived indicators and higher rates of agreement were found for the three highest LS levels (Canton, German-speaking Switzerland, further away). In our study, participants completed the LSQ daily, which contrasts with most studies assessing an individual's habitual life-space retrospectively only once a month presumably leading to more memory bias due to the longer reporting for a period.

4.1.2. pMOT and aMOT

We used a rule-based method comparable to other approaches in the literature (e.g., Vanwolleghem et al., 2016) that classifies 1-min move segments as pMOT or aMOT based on statistical features extracted from GPS and accelerometer data. A major limitation of the sensor-based indicators are periods with missing GPS data due to signal outage, other technical issues (empty battery, memory capacity) or participants leaving the devices at home that are therefore not identifiable as traveling (Nguyen et al., 2017). This might be one of the possible reasons for the considerable self-reported over-estimations (respectively the sensor-derived under-estimations) for pMOT and aMOT. We used end-of-day estimates of durations spent on pMOT and aMOT for the self-reported indicators. In the field of transportation, researchers typically ask for start and end times of the trips covered during a day and thereof derive total time spent in different MOTs (Panter et al., 2014; Vanwolleghem et al., 2016). This might be more accurate than our approach, however, also more time-consuming and more difficult to implement in studies involving a frequent assessment schedule over long time periods and a wide range of variables, as was the case in MOASIS. In the end-of-day questionnaire regarding pMOT and aMOT, we tried to instruct participants as clearly as possible that traveling activities with spatial displacements are of key interest. However, a potential source for self-reported over-estimations of aMOT might still be caused by participants accidentally adding moderate to vigorous physical activities (such as working in the garden, cycling in a gym) to the daily time spent on aMOT. Such activities, however, represent stationary activities and were therefore intentionally excluded by our pMOT/aMOT detection method.

Despite limitations regarding the accuracy from both types of assessment, we found moderate to large mean iCorrs of 0.51 and 0.36 for pMOT and aMOT, respectively. These results are in line with the ones of Vanwolleghem et al. (2016) who found correlations in the same order of magnitude that are lower for number of walking/cycling trips (r = 0.25 to 0.30) than for number of pMOT trips (r = 0.57 to 0.59). Research published so far did not show a clear pattern of systematic under- or over-reporting using self-reported or sensor-based techniques to assess mobility (Houston et al., 2014; Vanwolleghem et al., 2016). However, more evidence (e.g., Kelly et al., 2013; Klous et al., 2017; Panter et al., 2014) was found that self-reported indicators generally tend to overestimate traveling durations which is in line with our results. We found a clear trend towards self-reported overestimations for both pMOT (*Mdn* = 25.0 min) and aMOT (*Mdn* = 45.0 min) (cf. Table 5). Houston et al. (2014), who published the only paper we are aware of comparing daily reported to sensor-derived times of traveling, found similarly clear tendencies for over-reporting of walking (49%). In our study we found this trend even more markedly, with a percentage of 72% of self-reported over-reporting regarding aMOT (see Table 6). Also, for pMOT our results show that in more than half of the cases (59%), self-reported indicators overestimate traveled distances by at least 10 min. Based on the agreement threshold of ± 10 min, we found more days in agreement for pMOT (23%) than aMOT (13%).

4.2. Comparisons across all mobility parameters

It is interesting that, independent of the assessment method, LS is moderately to largely correlated with pMOT, which is a more fine-grained measure of mobility (*M* iCorrs between 0.49 and 0.67). This finding suggests that a comparison between studies using more life-space-oriented assessments and studies assessing travel durations in order to describe the degree of mobility is at least partially feasible. It makes sense that a higher amount of pMOT is more determining for a higher LS indicator than aMOT. In order to reach a higher LS level, increasingly larger distances need to be covered that are of an order of magnitude typically only feasible with pMOT. At the same time, we can expect to find a large variation of durations of aMOT within one life-space level (e.g., municipality).

4.3. Socio-demographic characteristics associated with estimation accuracies

Discrepancies between self-reported and sensor-derived mobility indicators can be explained by inaccurate reflection of a person's mobility by either the sensor-derived and/or the self-reported indicators. We investigated whether certain socio-demographic and mobility-relevant characteristics have an influence on indicator correspondence (reflected by the iCorrs) and discuss whether the accuracy of the sensor-derived and/or the self-reported indicator might have been affected by the respective characteristics.

Despite the small sample size for the analyses on the between-person level (n = 27), we found that people with the availability of a car have significantly higher probabilities for days with agreement in the pMOT indicators. This finding is in line with that of Houston et al. (2014). One possible explanation for this result is that people who do not use a car might cover more distances using trains, which often do not add up to the sensor-derived pMOT indicator (as the GPS signal is often lost in trains). Therefore, person-days that include a large portion of train rides in their self-reported pMOT estimates might easily be overestimated by the self-reported, or rather underestimated by the sensor-derived indicators. Another possible explanation might be that people traveling by car instead of public transport are more aware of how much distance they cover. When traveling by public means of transportation, individuals are often performing other activities (e.g., reading, sleeping) and might therefore be less aware of the actual distance traveled. Furthermore, we found a (non-significant) tendency for higher income and education groups to have higher indicator agreements regarding the LS and aMOT indicators. Comparable results were found by Houston et al. (2014) and Neven et al. (2018). A hypothesis that would need to be further investigated is that people with higher education levels have a greater capacity to engage in the cognitive task of estimating their daily mobility.

In future research, it would be interesting to investigate whether trip-based characteristics derivable from GPS data (transportation mode, trip length, daily number of trips etc.) have an impact on indicator agreement. Nguyen et al. (2017) and Neven et al. (2018) found, for example, that individuals who tend to do more trips overall have a higher probability of omitting trips in their diaries.

4.4. Complementarity of self-reported and sensor-derived mobility indicators

Both assessment methods have advantages and drawbacks. Self-reported assessment usually involves more participant burden in terms of active involvement. Moreover, responses are subjective and are prone to memory biases as well as estimation errors (Birenboim and Shoval, 2016; Blanchard et al., 2010). Most of the drawbacks, however, can also be seen as advantages. Subjective self-reports give insights into how particular behaviors/quantities etc. are perceived by individuals. It is possible to capture more information about the context or meaning of a particular activity. Information for long time periods can be assessed in a single point in time, retrospectively. Moreover, the assessment is less technology-dependent. In our sample, we had considerably more complete self-reported (n = 707, 691, 686) than sensor-derived (n = 423, 401, 401 for LS, pMOT, aMOT, respectively) information. This is in line with Neven et al. (2018), who found that more trips were not registered by GPS rather than by self-reported trip diaries.

In sensor-based assessment, weaknesses include technical issues and limitations when collecting sensor data; lack of compliance of participants leading to missing data; and lack of consensus regarding the mobility indicators to be derived from sensor data as well as the methods used for this purpose. On the other hand, sensor data can be cheaply collected, and the quality of the mobility indicators can be expected to continuously improve. Sensor data will improve (e.g., less missing data) as a result of technological advancements (more memory capacity, longer battery life, or more user-friendly device handling). Furthermore, methods to extract more accurate and diverse indicators representing mobility information are constantly improving (e.g., Cetateanu et al., 2016; Hirsch et al., 2014).

Irrespective of technical capacities and limitations, self-reports and sensor-derived indicators also provide different perspectives on mobility. It is unclear whether one's self-reported perception of being an active, mobile person is differently related to health indicators (e.g., physical fitness, well-being, etc.) than sensor-based (thought to be "objective") mobility indicators (that may or may not correspond to the self-reported perceptions). It remains to be tested which type of mobility indicators assessed with which method are most meaningful in different health contexts. If resources are available, we suggest using both data sources, complementing each other to obtain a dataset that is as complete and as multi-faceted as possible. As this is not always possible, however, studies such as this one can help guiding decisions about which assessment method to prioritize.

5. Conclusion

We proposed a methodology to compute three mobility indicators often used in aging and health research — LS, pMOT, and aMOT — based on sensor data (GPS, accelerometer) collected over 30 days in healthy older adults. We then did comparisons between sensor-derived measures and their corresponding self-reported counterparts as well as across all mobility indicators. Further, we investigated whether we find associations between estimation accuracies (reflected by the participants' iCorrs) and their socio-demographic characteristics.

We found moderate to large positive mean iCorrs between the respective self-reported and sensor-derived indicators ($r = 0.75$ for LS, 0.51 for pMOT and 0.36 for aMOT). For life-space, the overall accuracy is rather high, with 58% of the person-days having completely overlapping self-reported and sensor-based indicators. This suggests that the life-space questionnaire may to a large degree be substituted by GPS assessments, if reliable GPS data are available. For the indicators reflecting travel durations using pMOT and aMOT, in most of the study days (i.e., 59% and 72%, respectively) self-reports over-reported, whereas sensor-derived measures under-reported the amount of mobility. According to our results, a higher degree of agreement between self-reported and sensor-derived indicators of pMOT is to be expected for individuals having access to a car. The slight tendency for positive correlations between education and indicator correspondence for LS and aMOT should be followed up in a study including more participants to achieve greater statistical power on the between-person level.

Mobility is key to healthy aging. Having the opportunity to use sensor-based assessments complementarily to the traditional self-reports is promising as they are 'objective' (i.e., not prone to memory or reporting biases), require no active participant involvement and observations could thus be easily extended over long time periods. Against this background, when making use of such indicators in a health or aging context, findings such as the ones reported in this paper help researchers to assess the magnitude and direction of potential differences in mobility variables depending on the assessment method as well as on personal and socio-demographic characteristics of the individuals. In future research, it remains to be tested which combinations of indicators and assessment techniques are most associated with individuals' health outcomes.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2018.11.010.

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